NOTES D'ÉTUDES

ET DE RECHERCHE

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Assessing Aggregate Comovements in France, Germany and Italy Using a Non Stationary Factor Model of the Euro Area*

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Résumé.

L'objectif de ce papier est d'étudier le degré de co-movement entre l'Allemagne, la France et l'Italie. Nous utilisons une base de données comprenant un grand nombre de séries non stationnaires et concernant les pays de la zone euro afin de mesurer l'effet des chocs communs par rapport aux chocs spécifiques et des chocs transitoires par rapport aux chocs permanents sur la période 1980:1 à 2003:4. Nous appliquons une méthologie développée par Bai (2004) et Bai et Ng (2004) pour construire un indicateur coincident du cycle des affaires dans la zone euro, auquel les cycles nationaux apparaissent de plus en plus corrélés au cours du temps pour les mouvements périodiques compris entre 8 et 32 trimestres, alors que des différences importantes subsistent pour les mouvements périodiques plus longs et qui mesurent la croissance potentielle. Cet indicateur est aussi corrélé aux cycles économiques hors zone euro.

Mots-Clés : Modèles à facteurs, modèles de données de panels non stationnaires, cycles des affaires de la zone euro

Classification JEL : C12, C22

Abstract.

The objective of the paper is to investigate to what extent business cycles co-move in Germany, France and Italy. We use a large-scale database of non-stationary series for the euro area in order to assess the effect of common versus idiosyncratic shocks, as well as transitory versus permanent shocks, across countries over the 1980:Q1 to 2003:Q4 period. We apply the methodology proposed by Bai (2004) and Bai and Ng (2004) to construct a coincident indicator of the euro area business cycle to which national developments appear to be increasingly correlated at business cycle frequencies (8 to 32 quarters), while more significant differences appear at lower frequencies which measures potential growth. The indicator is also shown to be related to extra euro area economic developments

Keywords: factor models, non-stationary panel data models, euro area business cycles

JEL classification: C12, C22

Résumé non technique.

Le papier étudie le degré de comovement entre l'Allemagne, la France et l'Italie en utilisant une base de données comprenant un grand nombre des séries pour les pays de la zone euro sur la période 1980:1-2003:4. Nous construisons un Indicateur du Cycle des Affaires (ICA) auquel nous comparons les trois pays mentionnés ci-dessus afin de mesurer l'importance des chocs spécifiques par rapport aux chocs communs et de déterminer si les cycles de court terme de ces pays sont devenus plus corrélés au sein de la zone euro.

L'utilisation d'un tel indicateur à des fins d'analyse des cycles conjoncturels permet d'exploiter l'information contenue dans un grand nombre de variables macroéconomiques pour obtenir une meilleure représentation des mouvements cycliques. C'est l'intuition de la méthodologie développée par le National Bureau of Economic Research (NBER) aux Etats-Unis, tel que le décrit l'ouvrage de référence de Burns et Mitchell (1946). Cette méthodologie a été largement utilisé depuis lors (Zarnowitz, 1992).

La base de données concerne différents pays, ce qui permet d'extraire la composante commune aux évolutions économiques nationales. Cette approche a déjà adoptée dans la littérature utilisant les modèles à facteurs dynamiques. Stock et Watson (1998, 2002), Forni et alii (2000), Forni et Lippi (2001), Canova et alii (2004) en sont des exemples récents.

Le papier apporte une nouvelle contribution à cette littérature, avec, comme principale différence par rapport aux travaux précités, un raisonnement sur des séries en niveau (et non pas stationarisées par différenciation).

Nous mettons en oeuvre une analyse en composantes principales en utilisant le modèle à facteurs introduit par Stock et Watson et largement développé par Bai et Ng (2004) et Bai(2004) pour le cas de séries non stationnaires. Par ailleurs, l'inférence statistique est complète, grâce à la grande dimension du panel, à la fois individuelle et temporelle, ce qui, dans la litérature sur les ICA, constitue une amélioration majeure par rapport aux modèles à facteurs traditionnellement utilisés.

L'extraction des facteurs à partir de variables en niveau a plusieurs avantages: elle permet l'identification des tendances de long terme associées aux effets persistents des chocs et l'évaluation d'indicateurs statistiques pertinents associés au niveau des variables, comme les points de retournement dans la tradition de l'analyse "classique" du cycle des affaires, mise en

avant récemment par Hardin et Pagan (2002).

De plus, ce cadre d'analyse permet de déterminer si les sources de comovement sont transitoires ou permanentes et plus particulièrement si les déterminants de la croissance potentielle -associée à la composante permanente- sont communs ou, au contraire, spécifiques à chacun des pays. L'analyse fait ressortir trois facteurs communs non stationnaires, mais nous mettons l'accent sur le premier facteur comme source de croissance potentielle dans la mesure où il attribue des poids égaux à quasiment toutes les variables macroéconomiques de notre base de données et retrace donc bien, de ce fait leur dynamique commune. Nous identifions un petit nombre de facteurs pertinents pour analyser les fluctuations conjoncturelles dans les trois pays que nous étudions. Nous suggérons une décomposition de chacune des séries de PIB -prises en niveau- en trois parties: une partie commune persistente (obtenue par projection du PIB sur les facteurs communs non stationnaires), une partie commune transitoire (obtenue par projection sur les facteurs communs stationnaires) et une partie spécifique et transitoire. De façon à se concentrer sur le cycle des affaires, nous appliquons un filtre statistique à ces trois composantes et nous n'étudions donc que les mouvements périodiques de moyen terme (compris entre 8 et 32 trimestres). Une telle approche est comparable, dans son esprit, à l'analyse factorielle dynamique menée par Forni et Lippi (1998), mais nous n'identifions pas les facteurs dynamiques à partir d'une analyse spectracle comme le font ces auteurs.

Le réel apport de la méthologie de Bai et Ng appliqué à la construction d'un ICA réside dans l'extraction du premier facteur. Nous calculons un intervalle de confiance autour de la projection du PIB zone euro sur cet indicateur. Pour chacun des trois plus grands pays de la zone euro, nous mettons en évidence un accroissement de la corrélation du cycle des affaires depuis le milieu des années 1990, ce que nous opposons au comportement de la croissance potentielle dont nous montrons qu'elle reste significativement différente selon les pays. Nous mesurons aussi que l'indicateur établi par projection du PIB de la zone euro sur le premier facteur est bien corrélé avec le cycle des affaires aux Etats-Unis. Ceci indique -en cohérence avec l'analyse de Artis et alii (2004), de même que celle de Montfort et alii (2004)- que l'ICA sur la zone euro est corrélé aux cycles mondiaux dans le cadre du processus de mondialisation des économies.

Non technical summary.

The paper investigates to what extent business cycles co-move in Germany, France and Italy, using a large database for the euro area on the 1980Q1-2003Q4 period. We construct a Business Cycle Index (BCI) to which the three countries cycles are compared, in order to determine how important are common versus specific shocks, and whether individual countries' business cycles have become more correlated within the euro area.

Using a BCI for studying business cycles means relying on a large number of macroeconomic series in order to get a better representation of cyclical movements. This is the intuition behind the methodology developed by the National Bureau of Economic Research (NBER) in the US, as described in the seminal book of Burns and Mitchell (1946) and since then widely used (Zarnowitz, 1992).

The database includes series on different countries and enables to extract the common component to national economic developments. This is the approach already adopted in the literature which uses dynamic factor models. Recent examples are Stock and Watson (1998, 2002), Forni et al (2000) and Forni and Lippi (2001), Canova et al. (2004).

The paper is an additional contribution to that literature but the main difference with respect to previous studies stems from the choice to work with the levels of the series (and not on series that are transformed by first-differentiation to ensure stationarity).

Hence, we implement a principal component analysis using the factor model introduced by Stock & Watson (1998) and largely developed by Bai & Ng (2004) and Bai (2004) for the non-stationary case. Moreover, the inference is proved to be complete, thanks to the large panel and time dimensions, which is a major improvement in the BCI literature in comparison with previous factor models.

Working with levels has distinctive advantages: it permits to extract the long run trend associated with the persistent effect of shocks and to derive useful statistical indicators associated with the levels of the variables, like turning points in the tradition of the classical cycles as recently advocated by Harding and Pagan (2002).

Moreover, this framework allows to examine whether the sources of similarities are transitory or permanent and more particularly whether the determinants of potential growth -associated with the permanent component- are pervasive or country-specific. The analysis uncovers three non-stationary factors, but we give more emphasis to the first factor as a source of potential growth, since it weights equally all these macroeconomic variables and captures the overall trend embedded in them.

We identify a small set of relevant factors to explain the fluctuations of GDP at business cycle frequencies in the three countries under study. We suggest therefore a useful decomposition of each GDP series -taken in levels- into three parts: a common persistent part (obtained by projection of GDP onto the common non-stationary factors), a common transitory part (obtained by projection onto the common stationary factor) and an idiosyncratic (stationary and hence) transitory part. In order to focus on the business cycle, these three components are filtered and we only keep the business cycle frequencies (periodic movements between 8 and 32 quarters). Such results are comparable to the ones obtained by applying DFA as developed by Forni and Lippi (1998), but we do not identify the dynamic factors from a spectral analysis like these authors.

The real benefit of the application of the Bai and Ng methodology appears for the construction of our BCI from the first factor. We derive confidence band around the projection of euro area GDP on the indicator. We show, on the one hand, that the correlation of the cyclical components of the three largest euro area countries with the indicator has increased from the mid 1990s, indicating higher correlation of business cycle components. On the other hand, long run components, expressing potential growth remain different. We also show that the business cycle indicator on euro area GDP is well correlated with the lagged US indicator constructed according to the same methodology. This provides evidence, consistently with the analysis of Artis et al. (2004) and Montfort et al. (2004), that our euro area indicator is actually correlated with worldwide cycles in the context of globalization.

1 Introduction

The objective of the paper is to investigate to what extent business cycles co-move in Germany, France and Italy, using a large database for the euro area on the 1980Q1 to 2003Q4 period. We construct a Business Cycle Index (BCI) to which the three countries cycles are compared, in order to determine how important are common versus specific shocks, and whether individual countries' business cycles have become more correlated within the euro area.

Against a general trend towards more synchronisation between euro area countries, triggered by the 1979 European Monetary System, the 1992 Internal Market programme and the 1999 European Monetary Union -although authors disagree on the direction of causality- Germany, France and Italy have regularly experienced periods of divergence. For example, the 1980s and some portion of the 1990s were periods of higher divergence. On the contrary, the simultaneity of the world slowdown in 2001 surprised observers. The three countries have, since then, exhibited more significant asymmetries. To assess these comovements, or the lack thereof, one needs a common benchmark and a simple reference indicator.

First, regarding the common benchmark against which each country's cyclical position can be compared, Germany has often been seen as the obvious choice (see e.g. Artis and Zhang, 1999, or Angeloni and Dedola, 1999), although there was evidence that Germany was more correlated with 'Anglo-saxon' countries than France and Italy (Helbling and Bayoumi, 2003). Within the Single Currency Area, the sole reference to Germany is no longer warranted.

Second, with respect to the reference indicator to analyze cyclical features, it is usual to focus on a set of macroeconomic series, to filter them so as to extract its cyclical component, then to examine the correlations of the cyclical components across countries, taken contemporaneously or with lags or leads.

Such an approach usually requires to focus on a limited number of series, while many authors point out that a better representation of the cyclical movements can be captured from a large number of economic series. The idea is behind the methodology developed by the National Bureau of Economic Research (NBER) in the US, as described in the seminal book of Burns and Mitchell (1946) and since then widely used (Zarnowitz, 1992). The goal is to convert complex economic dynamics into one-dimensional figures, which leads to construct a BCI.

We adopt a multivariate approach with a view to characterizing the common part of the national economic dynamics. This is already the approach adopted in the literature which uses dynamic factor models. Recent examples are Stock and Watson (1998, 2002), Forni et al (2000) and Forni and Lippi (2001), Canova et al. (2004).

The paper is an additional contribution to this literature but the main difference with respect to previous studies stems from the choice we make to work with the levels of the series.

Hence, we implement a principal component analysis using the factor model introduced by Stock & Watson (1998) and largely developed by Bai & Ng (2004) and Bai (2004) for the non-stationary case. Moreover, the inference is proved to be complete, thanks to the large panel and time dimensions, which is a major improvement in the BCI literature in comparison with previous factor models.

Working with levels has distinctive advantages: it permits to extract the long run trend associated with the persistent effect of shocks and to derive useful statistical indicators associated with the levels of the variables, like turning points in the tradition of the classical cycles as recently advocated by Harding and Pagan (2002).

Moreover, this framework allows to examine whether the sources of similarities are transitory or permanent and more particularly whether the determinants of potential growth -associated with the permanent component- are pervasive or country-specific. The analysis uncovers three non-stationary factors, but we give more emphasis to the first factor as a source of potential growth, since it weights equally all these macroeconomic variables and captures the overall trend embedded in them.

The paper is therefore close to the one carried out by Eickmeier (2005), who also contributes to the literature on BCIs, by building such an indicator, studying cycles and trends based on stationary and non stationary factors. However, there are several differences. First of all, Eickmeier (2005) proposes a benchmark indicator based on "core" euro area countries while we consider all euro area countries. Second, using a different database, we manage to avoid differentiation of the variables before running the principal component analysis. In the end, not only do we get a different BCI, but also we perform a different identification of the factors. We use the Bai (2004) and Bai and Ng (2004) criteria to assess the number of non stationary factors, while she uses the Johansen test. She puts a lot of emphasis on comparing various variables to linear combinations of the factors (i.e. rotations), while we show, using the confidence interval derived by Bai (2004), that our first factor is close to euro area aggregate GDP in the 1990s.

We identify a small set of relevant factors to explain the fluctuations of GDP at business cycle frequencies in the different countries under study. We suggest therefore a useful decomposition of each GDP series -taken in levels- into three parts: a common persistent part, obtained by projection onto the common non-stationary factors, a common transitory part (obtained by projection onto the common stationary factor) and an idiosyncratic (stationary and hence) transitory part. In order to focus on the business cycle, these three components are filtered and we only keep the business cycle frequencies. Such results are comparable to the ones obtained by applying DFA as developed by Forni and Lippi (1998), but we do not identify the dynamic factors from a spectral analysis like these authors.

The real benefit of the application of the Bai and Ng methodology appears for the construction of our BCI from the first factor. We derive confidence band around the projection of euro area GDP on the indicator. We show, on the one hand, that the correlation of the cyclical components of the three largest euro area countries with the indicator has increased from the mid 1990s, indicating higher correlation of business cycle components On the other hand, long run components, expressing potential growth remain different. We also show that the indicator is well correlated with the lagged US indicator constructed according to the same methodology. This provides evidence, consistently with the analysis of Artis et al. (2004) and Montfort et al. (2004), that our euro area indicator is actually correlated with worldwide cycles in the context of globalization.

The paper is organized as follows. In section 2 we extract the common factors from the database in level, using the PANIC methodology. In section 3 we decompose GDP business cycles in three components. In section 4, we construct our euro area indicator and interpret it.

2 Extracting factors from a large-scale database: the PANIC approach

The goal of this section is to extract common trends from a large panel of non-stationary macroeconomic variables for the euro area. We identify trend components by referring to a non-stationary factor model and by using the PANIC (Panel Analysis of Non-stationarity in the Idiosyncratic and Common components) statistical procedure, recently developed by Bai and Ng (2004).

When the dimension of the panel (N) and the number of observation (T) both tend to infinity, approximate factor models are very convenient as the error term is allowed to be weakly cross-correlated across N as well across T and as consistent estimation of the space spanned by the common factors can be achieved by implementing a principal component analysis (PCA).

Accordingly, the estimation of such factor models involves a lower computational cost than the one of the Kalman filter, which is actually unfeasible as N and T are both large.

In the non-stationary case, the procedure of estimation is fairly the same as in the more common stationary case (Stock and Watson, 1998; Bai, 2003) and remains simple. Bai (2004) proves that a consistent estimator of factors obtains with the series in level even if they are integrated of order one, provided that the specific component is I(0) (see equation (5) below).

Under these assumptions, he proves more precisely that the estimators of the common factors (or stochastic trends) are uniformly consistent when N is sufficiently large relative to T (see proposition 1 in Bai, 2004).

As it can be seen from the Monte Carlo simulations in Bai and Ng (2004), the estimated factor space is far from the true one when the errors e_{it} are I(1). Hence the estimation of the factor using the data in level is not always consistent. This is the reason why Bai and Ng (2004) have proposed a machinery named PANIC in order to test whether the idiosyncratic part is I(0) or equivalently whether the source of non-stationarity is of common nature. Moreover, the PANIC methodoly provides estimates of the factors obtained by extracting principal components from the first differenced data.

However, when the errors are found to be I(0), the estimators of the factors obtained by using data in levels, are proved to be more efficient than the ones based upon first differencing and, in this case, one can straightforwardly assess the number of common trends.

In what follows, we first implement PANIC and we validate the stationarity of the idiosyncratic components, as estimated from the first differences of the series. Thus, we estimate the common trends by using the level of the data.

2.1 Data

We consider a database of 220 quarterly macroeconomic series for all euro area countries.

The data were initially compiled and described by Eickmeier (2005). They include data on national accounts GDP components, industrial production, employment, prices and wages, money and finance (share prices and interest rates) on the 12 euro area member countries (See Annex A). No euro area aggregate is icluded in the database. Data are quarterly and the period we consider is from 1980Q1 to 2003Q4. Hence the individual dimension is $N = 220$ and the time dimension T is equal to 91. The period is long enough to cover at least two entire business cycles. However, contrary to Eickmeier (2005), we consider all 12 euro area countries and not only the core set of 7 countries. In addition, we select the series that look sufficiently persistent in order to be I(1), while Eickmeier uses a mixture of I(0) and I(1) series. Such an exogenous and initial selection of our dataset explains that the factors we extract have different properties.

2.2 The factor model in the PANIC approach (Bai and Ng, 2004)

Let X be our (N, T) panel of quarterly macroeconomic variables. We assume that each variable X_{it} for $i = 1, ..., N$ depends on a few undelying factors F_t, either stationary or non stationary.

The model is the following:

$$
\begin{aligned}
X_{it} &= c_i + \beta_i t + \lambda_i' F_t + e_{it} && (1) \\
(1-L)F_t &= \alpha + C(L)u_t && (2) \\
(1-\rho_i L)e_{it} &= D_i(L)\varepsilon_{it} && (3)
\end{aligned}
$$

with $C(L) = \sum_{j=0}^{\infty} C_j L^j$ and $D_i(L) = \sum_{j=0}^{\infty} D_{i,j} L^j$, $\mathbf{F}_t = (F_{1t}, F_{2t}, \ldots, F_{kt})'$ and $\lambda_i' = (\lambda_1, \lambda_2, \ldots, \lambda_k)$. The u_t's and ε_t's are white noise.

The factors may contribute to the deterministic trend in the DGP through α but this parameter cannot be identified; indeed, in PANIC, the principal component method is applied to the differenced and demeaned data. So the specification of the deterministic component has no impact on the estimation of the factors and loadings.

The model allows r_0 stationary factors and r_1 common trends with $r = r_0 + r_1$. Equivalently, the rank of $C(1)$ is equal to r_1.

The idiosyncratic e_{it} is $I(1)$ if $\rho_i = 1$ and is stationary if $\rho_i < 1$.

The factors F_{jt} , $1 \leq j \leq r$, and the idiosyncratic components e_{it} may be either I(1) or I(0) and can even be integrated at different order[1]. When the dataset $\mathbf{X}_t$ encompasses I(1)-series only and when the idiosyncratic components (the e_i's) are I(0), one can conclude that the source of nonstationarity of variables is of common nature.

The processes $\eta_t = C(L)u_t$ and therefore the F_t's may contribute to the common "business cycle" component. This is the reason why we apply classical business cycle filters to the non-stationary factors in Section 3, when we examine the different sources of business cycle fluctuations.

2.3 Estimation and test

We turn now to the estimation and test procedures as proposed by Bai (2004) and Bai and Ng (2004).

When the residuals e_{it} are $I(0)$, it is possible to get consistent estimates of the factors and loadings $\mathbf{F}_t$, λ_i, respectively (Bai, 2004).

When it is not the case, - e_{it} are $I(1)$-, it is not longer true and Bai and Ng(2004) propose to run the principal component analysis on the first differenced series, specified as:

$$\Delta x_{it} = \beta_i + \lambda_i' \eta_t + \Delta e_{it}. \tag{4}$$

[1]It must be emphasized that a regression of x_{it} on $\mathbf{F}_t$ is spurious when e_{it} has a unit root, even if $\mathbf{F}_t$ is observed. The estimates of λ_i' and thus of e_{it} will not be consistent.

The estimates of $\mathbf{F}_t$ and e_{it} from (1) are thus obtained for $t = 2, \ldots, T$ and $i = 1, \ldots, N$ as:[2]

$$\widehat{F_{kt}} = \sum_{s=2}^{t} \widehat{\eta}_{ks} \tag{5}$$

$$\widehat{e_{it}} = \sum_{s=2}^{t} \widehat{\Delta e}_{is}, \tag{6}$$

Bai and Ng (2004) show that $\widehat{\mathbf{F}}_t$ and $\widehat{e}_{it}$ are consistent for $\mathbf{F}_t$ and e_{it}, respectively (see Lemma 2). Once the factors have been extracted, it is possible to identify the source of nonstationarity of the series.

First of all, one focuses on the idiosyncratic components $\widehat{e}_{it}$, as the inference procedure crucially depends on their stationarity.

Indeed, as recalled before, if they are found to be $I(0)$, according to Bai (2004), it is possible and more efficient to extract the factors directly from the levels of the variables.

So, one first runs the standard univariate $ADF_{\widehat{e}(i)}$ (Augmented Dickey-Fuller) for each idiosyncratic component e_{it}:

$$H_0 : d_{i0} = 0; H_1 : d_{i0} < 0 \tag{7}$$

where $\Delta\widehat{e}_{it} = d_{i0}\widehat{e}_{it-1} + d_{i1}$ and $\Delta\widehat{e}_{it-1} + \cdots + d_{ip}\Delta\widehat{e}_{it-p} + \xi_t$

It is worth noting that the distribution does not coincide with the one of Dickey Fuller (DF),[3] because of the linear trend in the data (see Bai and Ng (2004) for more details).

Then, one implements a pooled test procedure, in order to increase the power of the test:[4]

$$H_0 : \forall i, d_{i0} = 0, H_1 : \exists i, s.t. d_{i0} < 0 \tag{8}$$

Pooling is achieved in the lines of Choi (2001) for $N \to \infty$. If $p^c_{\widehat{e}}(i)$[5] denotes the p-value associated with $ADF_{\widehat{e}(i)}$, the test statistics is:

$$P^c_{\widehat{e}} = \frac{-2\sum_{i=1}^{N} \log p^c_{\widehat{e}}(i) - 2N}{\sqrt{4N}} \tag{9}$$

which is proved to be asymptotically distributed as $N(0, 1)$, provided that the idiosyncratic components e_i are independent.

In what follows, we will show that the idiosyncratic components $\widehat{e}_i$ can be considered as stationary according to a low value of the pooled P-value $P^c_{\widehat{e}}$.

[2]Notice that one observation is lost due to the first differencing of data.

[3]In fact, the ADF based upon an augmented autoregression has the same limiting distribution as the DF distribution if the number of lags is chosen such as $p^3/\min[N, T]$ (see Said and Dickey (1984) or Bai and Ng (2004)).

[4]Such a pooling test is known as being more efficient than a procedure using separately the series $\widehat{e}_i$. However, the gain of efficiency is effective only if there is no cross-section for the series of interest. Bai and Ng (2004) argue that a pooled test based upon $\widehat{e}_{it}$ is more appropriate than upon X_{it}, as long as the original series embody common components and thus are related to each other.

[5]The individual p-values $p^c_{\widehat{e}}(i)$ are obtained by simulation

Thus there are necessarily non-stationary factors, as the series are $I(1)$. In order to identify the number r_1 of common trends - that is non-stationary factors- Bai and Ng propose modified variants MQ of Stock and Watson's Q statistics, designed to test the number of common trends in a non-stationary multivariate dynamics.[6] However, the procedure supposes that the total number r of factors is known. [7] r is identified, by using information criteria proposed by Bai and Ng (2002) for the first-differenced series.

Before presenting the results, it is worth recalling that confidence intervals can be computed around any (true) underlying factor (or any linear combination of the factors) at each date t. For example, for the non-stationary factors, Bai (2004) proves that under the assumptions of absence of cross-section correlation for idiosyncratic errors, as $N, T \to \infty$ with $N/T^3 \to 0$:[8]

$$\frac{\sqrt{N\left(\widehat{\delta}'\widehat{\mathbf{F}_t} - Y_t\right)}}{\left[\widehat{\delta}' V_{NT}^{-1}\left(\frac{1}{N}\sum_{i=1}^{N}\widehat{e}_{it}^2\widehat{\lambda}_i\widehat{\lambda}_i'\right)' V_{NT}^{-1}\widehat{\delta}\right]^{\frac{1}{2}}} \rightarrow N(0,1) \tag{10}$$

where Y_t is the variable of interest, for example the GDP series, the parameter $\widehat{\delta}'$ rescales $\widehat{\mathbf{F}_t}$ toward Y_t via the following regression:

$$Y_t = \widehat{\delta}'\widehat{\mathbf{F}}_t + error \tag{11}$$

with $\widehat{e}_{it}^2$ denoting the estimated residuals $X_{ij} - \widehat{\lambda}_i'\widehat{\mathbf{F}_t}$ and V_{NT} is a diagonal matrix consisting of the first r largest eigenvalues of XX'/T^2N.

Such confidence intervals allow to assess, at each date t, how well a (true) factor component - that is an element of the space spanned by all factors F_t- can be approximated by an observed series Y_t.

2.4 Assessing common and idiosyncratic components

First, we run a principal analysis on the first differenced data and use the information criteria PC_2 and IC_2 proposed in Bai and Ng (2004) to determine the total number of factors. The former depends on an initial maximun number of factors, whereas the latter is invariant to this parameter. We choose these criteria since they prove to be more robust than the others, initially suggested by Bai and Ng (2002), when the residuals have serial-correlation.These criteria indicate that there are five factors which summarize the common information within data. The

[6]There are two Q statistics respectively associated with the cases where the non-stationary components of F_t are finite-order autoregressive processes and are more general processes including moving-average errors.

[7]This test involves a sequential procedure where, in the first step, m is fixed equal to r with a one unit decrease when the null hypothesis is rejected, *i.e.* $H_0 : r_1 = m$ against $H_1 : r_1 < m$. The critical values associated with these statistics are tabulated by Bai and Ng (2004) and are available from one to six factors.

[8]The previous results can be extended to the case where there are cross correlations in the residuals. The idea is to apply a White-type correction to consistently estimate the asymptotic variance matrix.

pooled test statistic ($P_{\hat{e}}^{c}$) is equal to 3.13 with the associated p-value of 0.00; the assumption of $I(1)$-residuals is thus strongly rejected.

The existence of more than one non-stationary factor might be seen as a surprizing result from a Real Business Cycle point of view, for which technology is the sole driving factor of the economy. Here we observe additional persistent shocks that can be viewed as demand shocks, or shocks that appear as non-stationary on the sample period considered.

Before extracting the common trends, we can summarize these preliminary results as following:

- *the data obey a factor structure which embodies a total number of 5 factors*;
- *the factors explain 39% of total variance of the database*;
- *the source of nonstationarity is not idiosyncratic, the forces driving trends in the Euro Area are only of common nature.*

An outstanding result concerns the loadings of all variables with respect to the first factor. By computing these loadings, one observes that the first non-stationary factor contributes to each of the 220 series with an almost constant loading (see Fig. 9 in Annex A). All the variables excluding interest rates contribute positively.[9] Apart from the German interest rates, the absolute value of the loadings of the variables range from 0.4% to 0.6%. The long term and short term German interest rates have the respective weights of -0.57% and -0.44% .

According to the fact that it represents an equally weighted average of the variables, we conclude that this unobservable variable is a synthetic variable which is a good candidate for a Business Cycle Index, in the lines, for example, of the US Conference Board index. It is therefore expected to provide a reliable synthesis of the economic fluctuations, as it can be seen in Marcellino (2005).

Being so comprehensive in nature, the first factor expresses the most persistent component included in the series. The negative loadings on interest rates only reflects the negative trend on interest rates, but it should be kept in mind that the total contribution of interest variables to factor 1 is less than 10%. The method, however, is not able to provide a really structural interpretation of the driving forces behind factor 1, similarly to the balance growth models where the main driving force results from a mixture of supply and demand shocks.[10]

[9]In the Figures displayed in Annex 2, variables are ranked on the x-axis in alphabetical order of the country, starting with Austria (AT) and finishing with Spain (SP), slight disadjustment were introduced to improve readability. The y-axis correspond to the loading in %, note that if all variables had the same weight, it would amount to 1/220, which is around 0.5%.

[10]Indeed, factors are linear combinations of the variables in the database, so that particular structural shocks on the variables have effects on the factors, and one may wish to assess whether shocks to the factors may be correlated to

The second factor opposes the real variables -except GDPs- to the nominal ones (CPIs, ULCs,...) (See Fig. 10 in Annex A).

Regarding the third factor, it generally opposes employment variables, private fixed capital formation and interest rates to the production variables. In that case, notice that the German long and short run interest rates highly contribute to the third factor, with 16.2% and 7.1%, hence a total of 23.3%, whereas the contributions of the other variables are at most 3.5%. To get a clearer picture, the German interest rate is excluded from Fig. 11 in Annex A.

Then we try to distinguish between persistent and stationary factors. In order to estimate the number of common trends, we compute two of the three criteria proposed by Bai (2004). From our dataset, we obtain three non-stationary factors. The other two common factors are therefore stationary.

We can summarize these additional results as following:

- *among the 5 common factors, 3 are non-stationary.*

3 The source of business cycle fluctuations

Referring to the 5 common factors we have identified, we now examine more closely the main sources of business cycle fluctuations. For that purpose, starting from our factor decomposition in level as given by equation (1), we look for a decomposition of each country business cycle along the different factors. In order to focus on the business cycle frequencies we apply the Christiano and Fitzgerald filter which is a linear filter and remove the highest and lowest frequencies. Empirical studies tend to prove that such a filter is closer to the ideal filter which perfectly retain the desired frequencies. Moreover with this filter, truncation appears to have a lower impact than the usual filters (HP, Baxter and King, 1995), provided the assumed underlying DGP (i.e. a random walk in our case) is correct (Christiano and Fitzgerald, 1999, Fournier, 2000). In contrast to first-differencing, this allows to retain as much information as possible. We decompose GDP in the various countries into the common and the idiosyncratic components. We end up measuring the contribution to the business cycle from (1) the common non-stationary factors ; (2) the common stationary factors ; (3) the idiosyncratic components.

For each variable X in country i, one can extract its cyclical component, $\widetilde{CX}_{it}$, by applying the Christiano and Fitzgerald filter onto the common and idiosyncratic components.[11] Let $\widetilde{CF}_{kt}$ be the cyclical components of factor k, by extracting the periodic movements between 8 and

underlying structural shocks, i.e. whether they represent, e. g. monetary policy shocks, or supply shocks, etc. However, such an analysis would require either to have access to an exogenous indicator of the shock (e.g. an index of monetary policy shocks, or technological shocks, etc.), or to run a full impulse response analysis. This is beyond the scope of the paper.

[11] The same analysis could have been carried out with another filter like the Hodrick-Prescott Filter.

32 quarters, and $\widetilde{CE}_{it}$ cyclical components of the idiosyncratic component of variables i. Since the filter is linear, $\widetilde{CX}_{it}$ can be decomposed according to:

$$\widetilde{CX}_{it} = \sigma_{X_i} * (\sum_{k=1}^{5} \lambda_{ik} * \widetilde{CF}_{kt} + \widetilde{CE}_{it}) \tag{12}$$

where σ_{X_i} has to be considered as a scaling factor.

The method proposed here is straightforward and consistent with the usual practice of identifying the business cycle from deviation to HP filtered-GDP for example.[12]

As usual, we are thus able to compute the share of the common/specific components in the business cycle. We can rewrite (12) as:

$$\widetilde{CX}_{it} = \widetilde{\Phi}_{i1t} + \widetilde{\Phi}_{i2t} + \widetilde{\Phi}_{i3t} + \widetilde{\Phi}_{i4t} + \widetilde{\Phi}_{i5t} + \widetilde{\xi}_{it} \tag{13}$$

where $\widetilde{\Phi}_{ikt} = \sigma_{X_i} * \lambda_{ik} * \widetilde{CF}_{kt}$ $(k = 1, \ldots, 5)$ are the common components of the variable i and $\widetilde{\xi}_i = \sigma_{X_i} * \widetilde{CE}_{it}$ the idiosyncratic one.

Furthermore, in computing the contribution of each common or idiosyncratic component $\widetilde{y}_{it}$ $\in \left\{\widetilde{\Phi}_{i1t}, \widetilde{\Phi}_{i2t}, \widetilde{\Phi}_{i3t}, \widetilde{\Phi}_{i4t}, \widetilde{\Phi}_{i5t}, \widetilde{\xi}_{it}\right\}$to the cyclical part $\widetilde{CX}_{it}$ of X_{it} , we only take into account the influence of $\widetilde{y}_{it}$ when $\widetilde{y}_{it}$ and $\widetilde{CX}_{it}$ have the same sign (i.e. both components point in the same direction, namely peaks or troughs). This a sort of generalisation of concordance indicator. Accordingly, at each date t, the contribution $A_{ikt}(\widetilde{y})$ is characterized, after normalization, as:

$$A_{ikt}(\widetilde{y}) = \frac{1_{sign(\widetilde{y}_{it})} . \widetilde{y}_{it}}{\sum_{k=1}^{5} 1_{sign(\widetilde{\Phi}_{ikt})} . \widetilde{\Phi}_{ikt} + 1_{sign(\widetilde{\xi}_{it})} . \widetilde{\xi}_{it}}, \tag{14}$$

$1_{sign(\widetilde{y}_{it})} = 1$ if $\widetilde{y}_{it}$ and $\widetilde{CX}_{it}$ have the same sign and $1_{sign(\widetilde{y}_{it})} = 0$ otherwise.

Thus we can decompose the fluctuations of the variables i into common and specific fluctuations whose contributions depend on the cyclical economic situation. Fig. 1 displays for France, Germany and Italy the cumulative contribution of each common factors and the idiosyncratic component to the cyclical part of the corresponding GDP ($X_i = GDP_i$ in equ. 12 and 13), that add-up to the business cycle component of GDP. In the previous section we pointed out that the first non-stationary factor offers a quite good description of the random walk component underlying, in particular, the German, French and Italian GDPs. In this section, we also notice that, at least for the GDPs, the first non stationarity factor is generally the main source of the common cyclical variation. In Germany, however, the third factor also plays a significant role.

In tables reported B1 and B2 in appendix B, one can read the shares of the common *versus* specific contributions to the business fluctuations for each of the 12 countries studied here, as

[12] The method that we implement assumes the constancy of the factor loadings over the sample period. According to Canova et al. (2004) this is not a too strong assumption, since, allowing for time-varying factor loadings in the analysis of the transmission of shocks in the euro area, the authors find that factor loadings turn out to be almost constant.

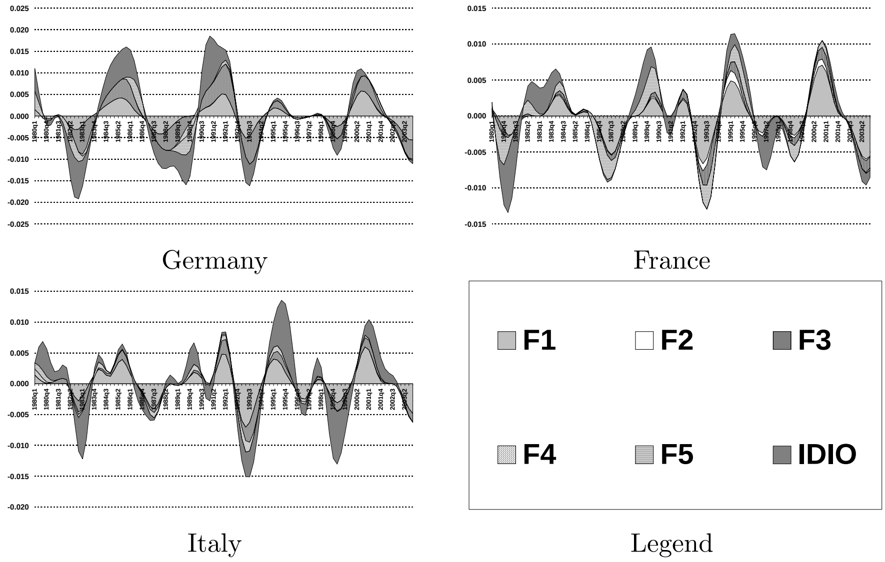


Figure 1: Contribution to concordance of business cycles

summarized by the GDP. The same kind of analysis could also by applied to other variables, like total employment. We have computed theses contributions over two sub-periods before and after 1992 in order to shed light on the convergence process.

We observe that the idiosyncratic part of the national business cycle is, in average, lower after 1993 than before. This is also the case for Germany, characterised as indicated before by a strong contribution of the third factor, as well as by the shock of German reunification in the first period. Specific-country cyclical movements remain also important, even over the most recent period, for Italy. It is interesting to note that the contribution of the first three non-stationary factors is the largest one, especially for the core countries in the European Union. This highlights the importance to take into account the common trend comovements in the characterization of the business cycle and in studying the convergence process.

We have also computed the shares of the different contributions over the last year 2003, in order to give an example of how to use the statistical procedure we propose to analyze current economic situation of the Euro area.

To summarize, it appears that the first factor is dominant. It explains a significant proportion of the variance of GDP for each of the three countries under study. Moreover its contribution is increasing over time. In the next section we therefore concentrate on the first non-stationary factor, that we use to build a coincident indicator of activity for the euro area.

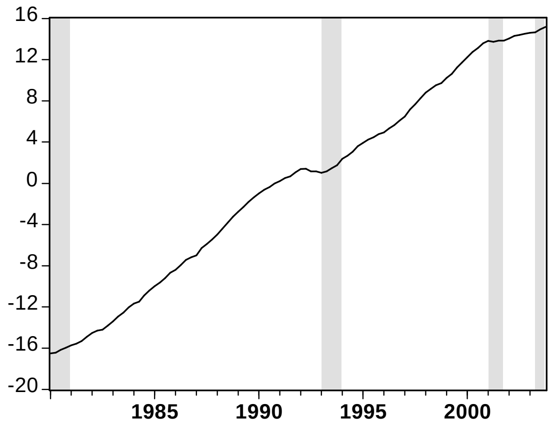


Figure 2: First common factor and peak/troughs derived from euro area GDP

4 Constructing a coincident indicator for the euro area

In the lines of the literature on the BCIs derived from factor models, we now use the first common factor to construct a new coincident indicator of the Euro area GDP. We first compare this indicator with the other indicators that are available. Then, following Bai (2004) and using the confidence interval around the factor, we test more rigorously its information content by examining whether different variables belong or not to the corresponding confidence interval. Stability over time and existence of correlation with external variables are finally considered.

4.1 A coincident indicator of GDP: descriptive analysis

In this subsection, we illustrate the ability of the first factor to reproduce the main features of euro area business cycles.

Fig. 2 displays the factor together with the expansion/recession periods derived from "classical business cycle" analysis in the line of Harding and Pagan (2002). It appears that indeed the 1993 recession and the early 2001 slowdown are well captured by the indicator.

Looking more precisely at the business cycle frequencies in Fig. 3, namely $\widetilde{CGDP}_i$ (with $i = FR, DE, IT$) and $\widetilde{CF}_1$, using the same notations as in section 3,[13] we observe that the indicator reproduces the main cycles of the three countries GDP. The dotted line is factor 1, while the solid line is the country GDP. The two troughs that appear in early 1980s and in 1993 are consistent with the Euro Area Business Cycle Dating Committee. However additional troughs appear also in 1987 as well as in 2002-2003.The main peaks appear during 1985, 1991, at the beginning of 1995 and in 2000.

Finally, as a complement to the previous analysis of the business cycle, it is also useful to

[13] $\widetilde{CX}$ is the series X observed at its business cycle frequencies (i.e. for periodic movements bteween 8 and 32 quarters).

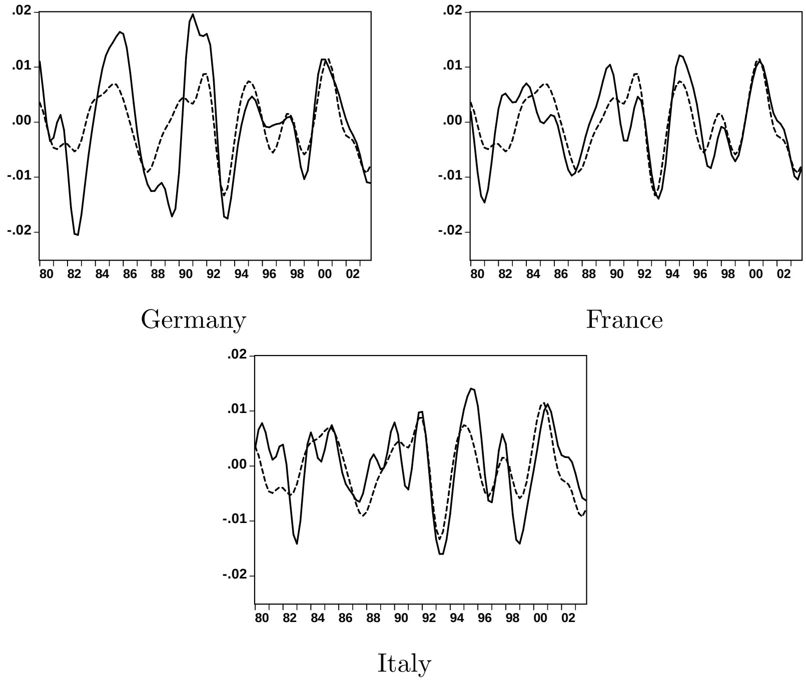


Figure 3: First common factor and GDP at business cycle frequencies

Table 1: Potential growth from long run frequencies

Country	1980Q1-1991Q4		1992Q1-2003Q4	
	mean	std dev.	mean	std dev.
France	2.1	0.9	1.8	1
Germany	2.3	1.4	1.4	0.4
Italy	2.1	1.4	1.5	0.6
F1	2.3	0.9	1.9	0.7

(*) periodic movements above 32 quarters

consider the lowest frequencies, namely the component of F_1 and GDP_i with periodic movements above 32 quarters, which provides a measure of euro area potential growth. As indicated in Table 1, performance differentials measured at long run frequencies have tended to increase. Indeed, potential growth was in average very similar across countries in the 1980s, between 2.1 % and 2.3 %, while the range has increased in the 1990s and early 2000's, between 1.4 and 1.8 %, with France tending to outperform the other three countries as from the second half of the 1990s. In addition, as shown in Fig. 4, there remains substantial differences in the cyclical pattern of potential growth, especially when compared to the first factor.

The conclusion of the section is that the first factor allows to distinguish between correlation of business cycles and growth differentials in the long run.

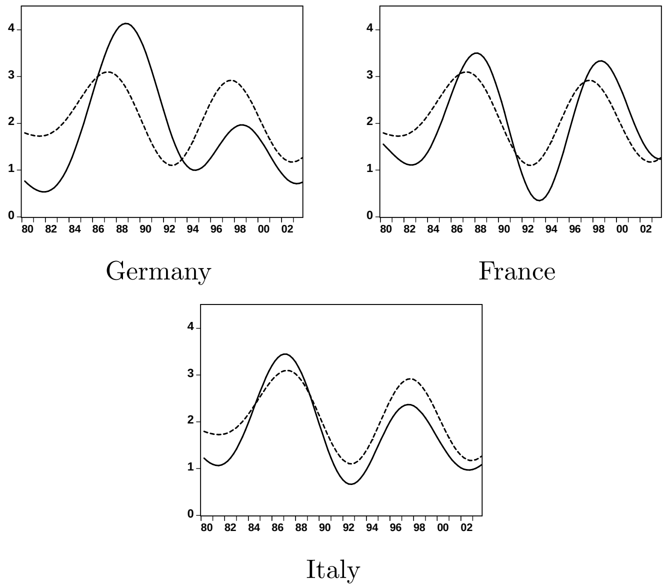


Figure 4: First common factor and GDP at long run frequencies

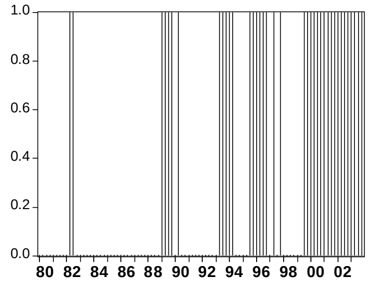


Figure 5: Periods when Euro Area GDP belongs to Conf. Interval around Factor 1

4.2 Interpreting the factor

Fig 2 showed that the trend in factor 1 was close to that of euro area GDP. We now examine more precisely such an hypothesis. As explained in section 2, one can use confidence intervals around any (true) factor component to assess how well it is approximated by an observed series, at each date t.

We can test, for example, whether the aggregate Euro Area GDP, GDP_{euro}, is close to a linear combination of the nonstationary factors. Indeed, comparing the first common factor (as exhibited in Fig. 2) and GDP_{euro}, it is easy to construct a 95% confidence interval for the linear combination $\delta' F_t$ which rescales F_t toward $GDP_{euro,t}$.

Fig. 5 displays the correspondance between Euro Area GDP and the first common factor. A vertical line at a given quarter indicates that euro area GDP belongs to the confidence interval.

The aggregate Euro Area GDP is often outside the 95% confidence interval around the trend: on average during the whole period it is within the band 40 percent of the time (4 quarters out of

10). However, the correspondence between the first factor and euro area GDP is increasing over time, as revealed in the more dense grid from 1992 onwards. In addition, the correspondance is very good since mid 1999.

4.3 Assessing stability over time

When looking at the intertemporal correlation of the first common factor with GDP in France, Germany and Italy, one can confirm the conclusion that it is a contemporaneous indicator. In addition, it is increasing when comparing the two subperiods.

For this purpose, we estimate the factors, and in particular factor 1, on the whole period, but we compare it to country GDPs for two subsamples : 1980-1991 and 1992-2003. We follow Stock and Watson (1999) by computing the instantaneous, lag and lead cross-correlations between the cyclical component of the first factor ($\widetilde{CF}_1$) and the country GDP ($\widetilde{CGDP}_i$). Fig. 6 displays $corr(\widetilde{CGDP}_{i,t}, \widetilde{CF}_{1,t+h})$ for each subsamples and for German, French and Italian business cycles. A maximum correlation at $h = 0$ indicates that the common cyclical component and business cycle of the country i tends to be synchronous, whereas a maximum correlation at , for example, $h = +1$, indicates that the cyclical component of the country i tends to lead the common cyclical component by one quarter.

Strikingly, we can clearly notice an increasing correlation between the first and the second subsample (1992-2003): while contemporaneous correlation is between 0.5 and 0.7 during the first period, it increases to around 0.9 in the second period.[14] Moreover, we can observe that, for one or two quarters, both the leads and the lags become correlated during the second period, while only leads or lags are correlated during the first period. Finally, the patterns of correlation are almost the same for each countries in the second subsample, whereas no common features appear from the first period. We interpret such a result of stronger dependence as a larger contribution of the CCI to national business cycles of each countries. In other words, countries have become more sensitive to the euro area shocks than before, what it is consistent with the convergence process occurring in the 1990s.

4.4 Comparing euro area and global business cycles

Finally, we consider non Euro area variables and investigate their correlation with our Euro area coincident indicator. When looking at US GDP at business cycle frequencies, there is evidence of significant correlation. Actually, Fig. 7 indicates that especially for the second subperiod, US GDP is rather leading the euro area (lead correlation is marked with dark boxes).

[14] We focus here on lead/lag correlations up to 4 quarters since above one year, correlation is likely to be spurious: with cycles of short duartion, long leads/lags may capture correlation with the following/previous cycle.

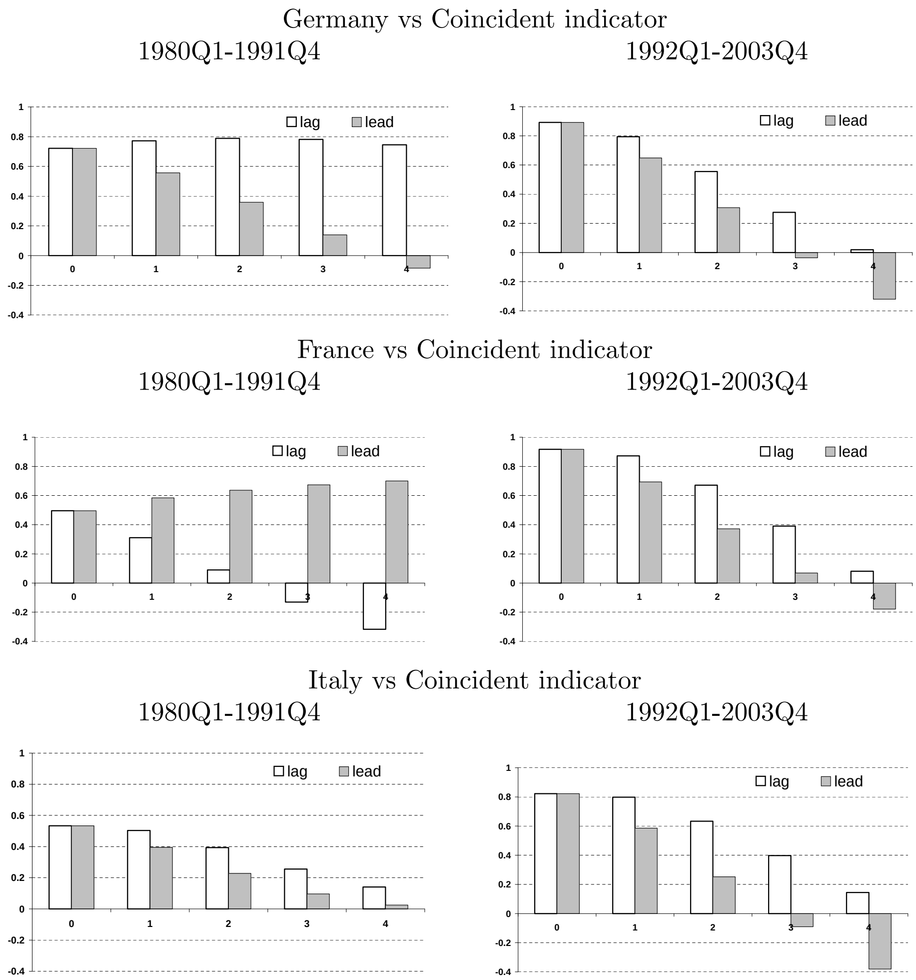
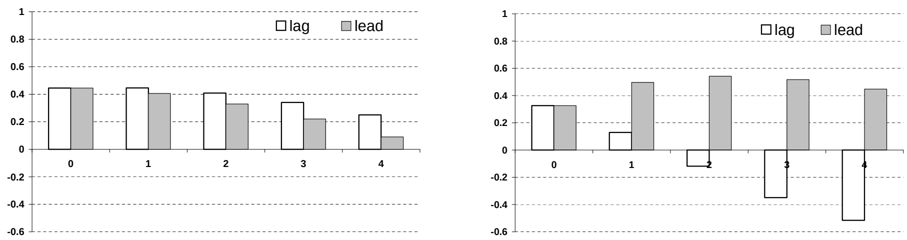


Figure 6: Correlation of national GDPs with factor 1 at bus. cycle frequency

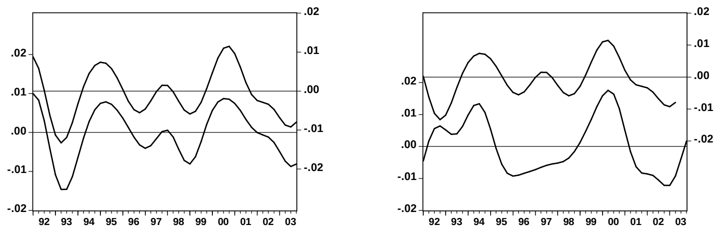
Fig. 8 below displays the dynamics of the filtered US GDP - shifted two quarters backwards- and the one of the Euro area coincident indicator over the second period. To compare the two series, we have used two different vertical scales and the origin of the scale is centered at two different levels, the top series (right-hand scale) is the common factor, while the bottom series (left-hand scale) is the business cycle component of GDP. The left figure corresponds to the Euro area GDP and the right figure to the US. While, obviously, the Euro area business cycle is close to factor one, as already discussed for the three main Euro area countries in Fig. 3 and 6, the largest fluctuations of the US GDP are also correlated with the common factor derived from the 220 euro area series, once moved forward by two quarters.

Similarly to what we did in section 3, it is possible to project any series outside the database on the five euro area factors and to compute the contributions of each of these factors. In table 2, we concentrate on our coincident indicator, which is the first common factor, and report its contributions only to filtered US and Euro area GDP. Consistently with the findings that the



1980Q1-1991Q4 1992Q1-2003Q4

Figure 7: Correlation between US GDP and fact. 1 at business cycle frequency



Euro area (lower) and CI(upper) USA (lower) and CI(upper)

Figure 8: GDP and fact. 1 at business cycle frequency (US moved forward by two quarters)

US GDP leads the euro area by two quarters, the coincident indicator has been moved forward by two quarters to compare it to the US. The coincident indicator appears to explain most of US GDP in the early 2000s (95% in 2003, as indicated in the table below).

All these results tend to prove the existence of common world shocks and corroborate the conclusions obtained by Artis et al. (2004) and Montfort et al. (2004), regarding the correlation of business cycles in the US and the Euro area.

5 Conclusion

In the paper we apply a large-scale factor model recently developed by Bai (2003 and 2004) and Bai and Ng (2004) to extract common stationary and non-stationary factors in the euro area. It turns out that we are in the right case where the factors can be extracted from the database

Table 2: Shares of business cycle explained by factor 1

Country	**Period**	**Coincident Indicator**
Euro Area	1993Q1-2003Q4	53%
	over 2003	71%
United-States$^{(1)}$	1993Q1-2003Q4	49%
	over 2003	95%

(1) the coincident indicator (first common factor) has been shifted forward by two quarters to be compared to the US case

in levels, as the idiosyncratic component identified according to the PANIC methodology are found to be stationary. We find that the euro area economies share three common non-stationary factors. The first one is close to the Euro area aggregate GDP in the second part of the sample. We suggest a way to decompose the cyclical fluctuations of each of the three countries under study, by filtering the different components - the non-stationary common one, the stationary common one and the idiosyncratic one- using the Christiano Fitzgerald filter.[15] We also use the first common factor to build a coincident indicator of the euro area that constitutes a benchmark against which country developments can be compared. We show that the common persistent movements significantly contribute to the common cyclical fluctuations, especially since the 1990's, pointing to increasing comovements. At the same time, the low frequency components -that can be associated with potential growth- exhibit more significant differences. In particular the first factor allows to distinguish between correlated business cycles and growth differentials in the long run.

These features could not have been pointed out if one had worked with the first differences series directly. This is the main advantage of using dynamic factor models estimated from a large non-stationary data set. More generally, the statistical tool we use appears to be useful to compare the behavior of the different countries over different periods and for various key macroeconomic variables, allowing for an economic interpretation of what is common/versus specific in the behavior of a European country, and what has a permanent/versus transitory effect.

Regarding further research, notice, that we have just focused on the analysis of activity, as summarized by GDP series. One way forward is obviously to implement the same kind of analysis by decomposing other types of series : employment, industrial production indexes and so on. (See table A3 for example). This gives interesting results to identify the sources of specific/versus common behavior for each European country vis-à-vis a common benchmark.

References

Angeloni I, Dedola F (1999) From the ERM to the Euro. European Central Bank, Working paper

Artis M, Osborn D, Perez-Vazquez P (2004) The International Business Cycle in a Changing World: Volatility and the Propagation of Shocks in the G-7. CEPRCentre for Economic Policy Research) Discussion Paper 4652

Artis M, Zhang M (1999) Further evidence on the international business cycle and the ERM. Oxford Economic Papers, 51:120–132

[15] In order to assess the impact of the factors to business cycles, as implemented in section 3, a further refinement has been to restrict the analysis to cycles of significant magnitude.

Bai J (2003) Inference in Factor Models of Large Dimensions. Econometrica 71:135–171.

Bai J (2004) Estimating Cross-Section Common Stochastic Trends in Non-stationary Panel Data. Journal of Econometrics, 122(1), 137-184.

Bai J and Ng S (2002) Determining the Number of Factors in Approximate Factor Models. Econometrica 70:191–221.

Bai J, Ng S (2003) A PANIC Attack of Unit Root and Cointegration, Econometrica

Baxter M, King RG (1995) Measuring Business Cycles Approximate Band-Pass Filters for Economic Time Series. NBER Working Paper, 5022

Burns AM, Mitchell WC (1946) Measuring Business Cycles. NBER, New York

Canova F, Ciccarelli M, Ortega E (2004) Similarities and Convergence in G7 Cycles. CEPR Discussion Paper, 4534

Choi I (2002) Combination of Unit Root Tests for Cross-Sectionally Correlated Panels. Mimeo, Kong Kong University of Science and Technology

Christiano LJ, Fitzgerald TJ (1999) The Band Pass Filter. NBER Working Paper, 7257.

Eickmeier S (2005) Common stationary and non-stationary factors in the Euro Area analyzed in a large-scale factor model. Mimeo, Deutsche Bundesbank, Economic Research Center

Forni M, Hallin M, Lippi M, Reichlin, L (2000) The generalized dynamic-factor model : identification and estimation. The Review of Economics and Statistics, 82(4):540–554

Forni M, Lippi M (2001) The Generalized Factor Model: Representation Theory. Econometric Theory, 17:1113–41.

Fournier JY (2000) L'approximation du filtre passe-bande propos[́]ee par Christiano et Fitzgerald. INSEE Working Paper

Giannone D, Reichlin L, Sala L (2002) Tracking Greenspan: Systematic and Unsystematic Monetary Policy Revisited. CEPR Discussion Paper, 3550

Harding and Pagan (2002) Synchronisation of cycles, Melbourne Institute of Applied and Social Research,

Helbling T, Bayoumi T (2003) Are they all in the same boat? the 2000-2001 Growth Slowdown and the G7 cycle linkages. IMF Working Paper, 46

Hodrick RJ, Prescott E (1980) Post-war U.S. Business Cycles: An Empirical Investigation. Working Paper, Carnegie-Mellon University

Marcellino M (2005) Leading Indicators: What Have We Learned? CEPR Discussion Paper, 4977

Monfort A, Renne J, Rüffer R, Vitale G (2003) Is Economic Activity in the G7 Synchronized? Common Shocks versus Spillover Effects. CEPR Discussion Paper, 4119

Stock JH, Watson, M (1988) Testing for Common Trends. Journal of American Statistical Association, 83:1097–1107.

Stock JH, Watson M (1998). Diffusion Indexes, NBER Working Paper, 6072

Stock JH and Watson M (1999) Business Cycle Fluctuations in US Macroeconomic Time Series. In: Rautenstrauch C, Seelmann-Eggebert R, Turowski K (eds) Handbook of Macroeconomics. Springer, Berlin Heidelberg New York

Stock JH and Watson M (2002) Macroeconomic forecasting using diffusion indexes. Journal of Business and Economic Statistics 20(2):147–162.

Zarnovitz M (1992) Business cycles: Theory, History, Indicators and Forecasting. Springer, Berlin Heidelberg New York

A Data and factor loadings

Table A1 : Mnemonics of the variables in the database

Mnemonics	Type of Variables
	National Accounts
gdp	*GDP, volume*
ge	*Government Consumption, volume*
exp	*Exports of goods and services, volume*
imp	*Imports of goods and services, volume*
pcfe	*Personal Consumer Expenditure, volume*
pnrfcf	*Private-sector non-residential Investment, volume*
ptfcf	*Private Total Fixed Capital Formation, volume*
tde	*Total domestic expenditure, volume*
	Employment
demp	*Total Employees*
temp	*Whole economy employment*
	Prices and Wages
cpi	*Consumer price, harmonized*
gdpd	*Gross domestic product, deflator, market prices*
comp	*Compensation to Employees, total*
ulc	*Unit Labour Cost*
	Production Index
ip	*Industrial production*
ipc	*IIP Consumer Durable*
ipm	*IIP Manufacturing*
ppi	*PPI Manufacturing Industry Index*
	Money and Finance
lti	*Long-term interest rate on government bonds*
sti	*Short-term interest rate*
m1	*M1 aggregate*
m3	*M3 aggregate*
mst	*Share Price*

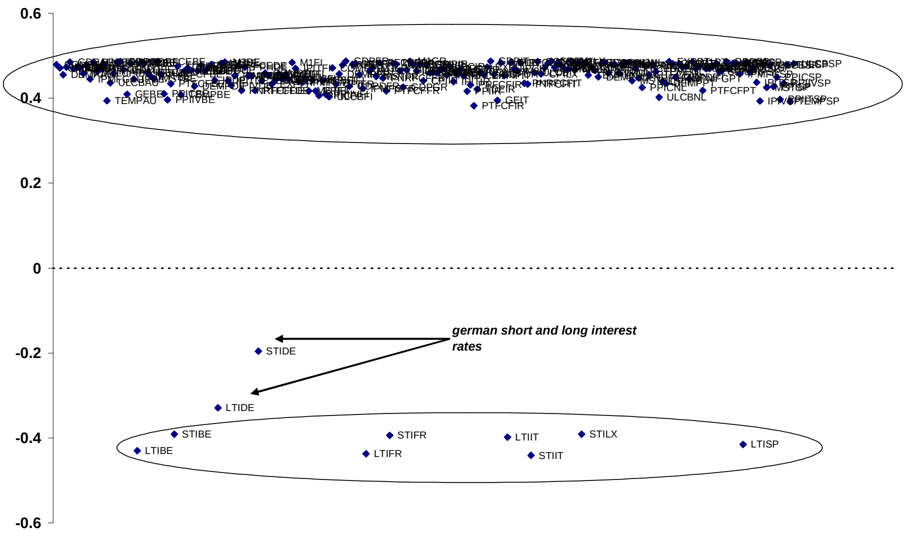


Figure 9: Contribution of variables to first common factor (%)

Table A2 : Mnemonics of the countries in the database

Mnemonics	Country
AU	*Austria*
BE	*Belgium*
FI	*Finland*
FR	*France*
DE	*Germany*
GR	*Greece*
IR	*Ireland*
IT	*Italy*
LX	*Luxembourg*
NL	*Netherlands*
PT	*Portugal*
SP	*Spain*

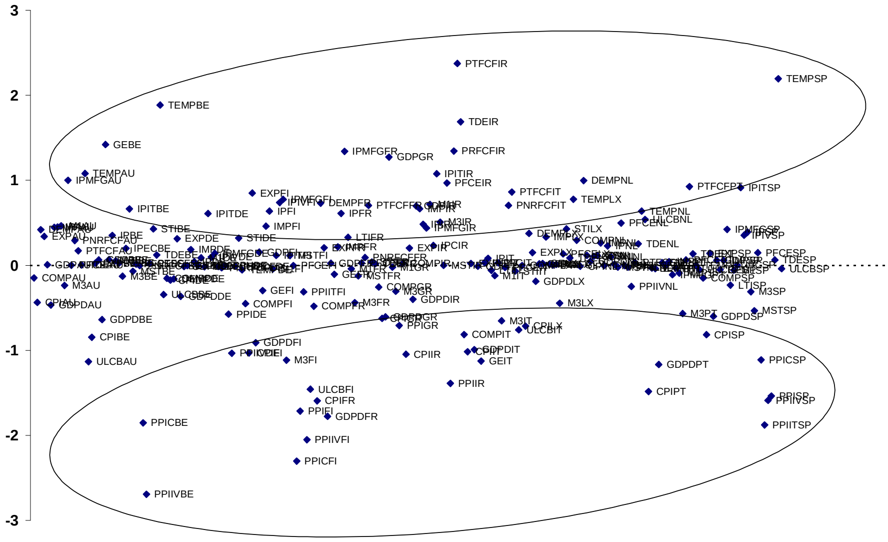


Figure 10: Contribution of variables to second common factor (%)

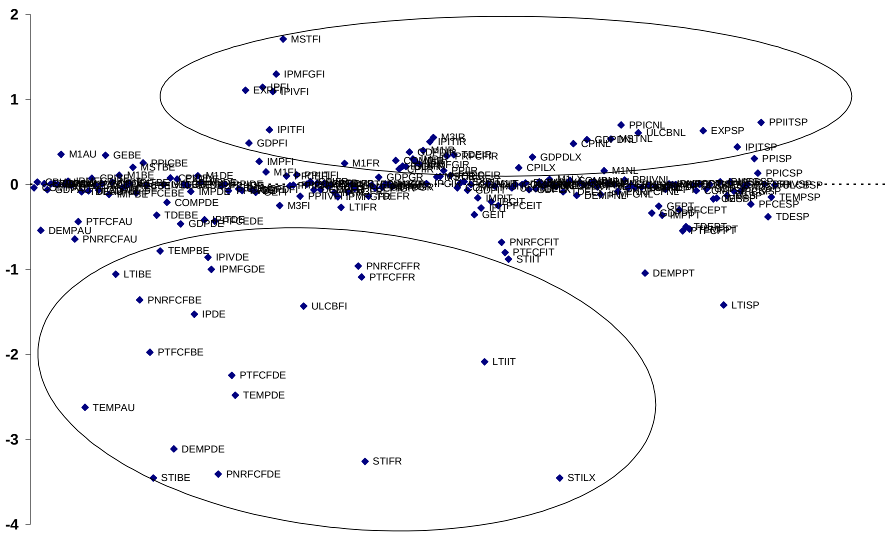


Figure 11: Contribution of variables to third common factor (%)

B Contributions of factors to GDP at business cycle frequency

Table B1: Shares of business cycle explained by common and specific component[a,b]

Country	Period		Common					Specific
			F1	*F2*	*F3*	*F4*	*F5*	e_i
	1980Q1-1992Q4		32%	2%	14%	4%	7%	42%
AUSTRIA	1993Q1-2003Q4		43%	4%	14%	2%	6%	32%
	over 2003	▽	75%	1%	21%	1%	2%	0%
	1980Q1-1992Q4		33%	6%	13%	2%	5%	40%
BELGIUM	1993Q1-2003Q4		35%	8%	11%	1%	3%	41%
	over 2003	▽	53%	3%	15%	2%	0%	26%
	1980Q1-1992Q4		10%	1%	13%	21%	28%	27%
FINLAND	1993Q1-2003Q4		17%	6%	6%	20%	28%	23%
	over 2003	−	54%	5%	8%	12%	8%	13%
	1980Q1-1992Q4		28%	2%	11%	0%	23%	36%
FRANCE	1993Q1-2003Q4		40%	6%	13%	0%	14%	27%
	over 2003	▽	62%	2%	17%	0%	1%	17%
	1980Q1-1992Q4		20%	0%	26%	5%	12%	37%
GERMANY	1993Q1-2003Q4		35%	1%	32%	6%	9%	17%
	over 2003	▽	45%	0%	35%	1%	3%	2%
	1980Q1-1992Q4		15%	12%	2%	4%	22%	47%
GREECE	1993Q1-2003Q4		8%	12%	6%	4%	24%	46%
	over 2003	△	0%	0%	13%	3%	4%	80%

[a] Business cycles extracted from GDP

[b] Symbols, ▽, △, − refer to a negative, positive, null output gap respectively

Table B2: Shares of business cycle explained by common and specific component (end)[a,b]

Country	Period		Common					Specific
			F1	*F2*	*F3*	*F4*	*F5*	e_i
	1980Q1-1992Q4		26%	14%	10%	7%	16%	26%
IRELAND	1993Q1-2003Q4		25%	19%	3%	7%	17%	29%
	over 2003	▽	66%	13%	0%	1%	1%	19%
	1980Q1-1992Q4		30%	0%	15%	7%	4%	43%
ITALY	1993Q1-2003Q4		32%	1%	11%	4%	1%	50%
	over 2003	▽	74%	0%	21%	4%	1%	0%
	1980Q1-1992Q4		30%	3%	12%	3%	13%	39%
LUXEMBOURG	1993Q1-2003Q4		34%	6%	8%	3%	12%	38%
	over 2003	▽	66%	2%	18%	1%	2%	11%
	1980Q1-1992Q4		26%	6%	4%	5%	16%	42%
NETHERLANDS	1993Q1-2003Q4		44%	14%	4%	4%	15%	19%
	over 2003	▽	52%	4%	4%	0%	3%	37%
	1980Q1-1992Q4		14%	0%	15%	2%	6%	62%
PORTUGAL	1993Q1-2003Q4		23%	3%	23%	2%	4%	45%
	over 2003	▽	57%	2%	38%	0%	2%	0%
	1980Q1-1992Q4		36%	5%	14%	0%	5%	40%
SPAIN	1993Q1-2003Q4		52%	11%	19%	0%	9%	9%
	over 2003	▽	76%	4%	20%	0%	0%	0%

[a] Business cycles extracted from GDP

[b] Symbols, $\bigtriangledown$, $\bigtriangleup$, $-$ refer to a negative, positive, null output gap respectively

Notes d'Études et de Recherche

1. C. Huang and H. Pagès, “Optimal Consumption and Portfolio Policies with an Infinite Horizon: Existence and Convergence,” May 1990.

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